Determining offshore wind installation times using machine learning and open data

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SUMMARY

During the last decade investments in offshore wind have increased while the cost per MW capacity has decreased significantly. Historically, offshore wind has relied on subsidies, but with the rapidly decreasing costs such schemes are no longer necessary. However, potential for cost reduction remains and should continuously be pursued to drive the transition to a fully sustainable energy system.

The installation process of offshore wind requires the use of expensive jack-up vessels. These vessels regularly report their position via the Automatic Identification System (AIS), which is a radio transponder technology developed for real-time vessel tracking to avoid collisions at sea. The AIS data offers accurate position data at a high time resolution and years of data is globally available at low cost.

This paper introduces a novel approach of applying machine learning to AIS data from jack-up vessels. We derive detailed time breakdowns of individual turbine installations, the variation within parks and vessel performance profiling. The algorithm is highly automated and requires no prior knowledge of individual turbine locations. Installation times and turbine locations can be inferred directly by applying a clustering algorithm to publicly available AIS data. These results can reduce the cost uncertainty when planning future offshore projects, which, in turn, improves the profitability of these projects.

INTRODUCTION

The installed capacity of offshore wind has increased by more than a factor of 10 during the last decade [1], and is expected to keep growing in the future [2]. Simultaneously, the global weighted average Levelized Cost of Energy (LCOE) for offshore wind decreased by 20% from 2010 to 2018 [3]. Until recently offshore wind has relied on government subsidies, but with the recent non-subsidized bids driven by cost reductions such schemes are becoming less important [4, 5]. However, potential for cost reduction remains and should be continuously pursued to drive the transition to a fully sustainable energy system.

The installation process of offshore wind turbines requires the use of jackup vessels with day-rates exceeding 100.000 € [6]. These vessels regularly report their position via the Automatic Identification System (AIS), a radio transponder technology developed for real-time vessel tracking to avoid collisions at sea [7]. The AIS data offers accurate position data at a high temporal resolution and years of data is globally available either publicly or at low cost [8, 9].

This paper introduces a novel approach to determining offshore installation times by applying machine learning to AIS data from jackup vessels. We derive detailed time breakdowns of individual turbine installations, the variation within parks as well as the time spent in transit and docked in harbor. The new method requires no prior knowledge of individual turbine locations. Installation times and turbine locations can be inferred directly by applying a clustering algorithm to publicly available AIS data. These results can reduce the uncertainty of costs when planning future offshore projects and thereby reduce overall project costs [10, 11].

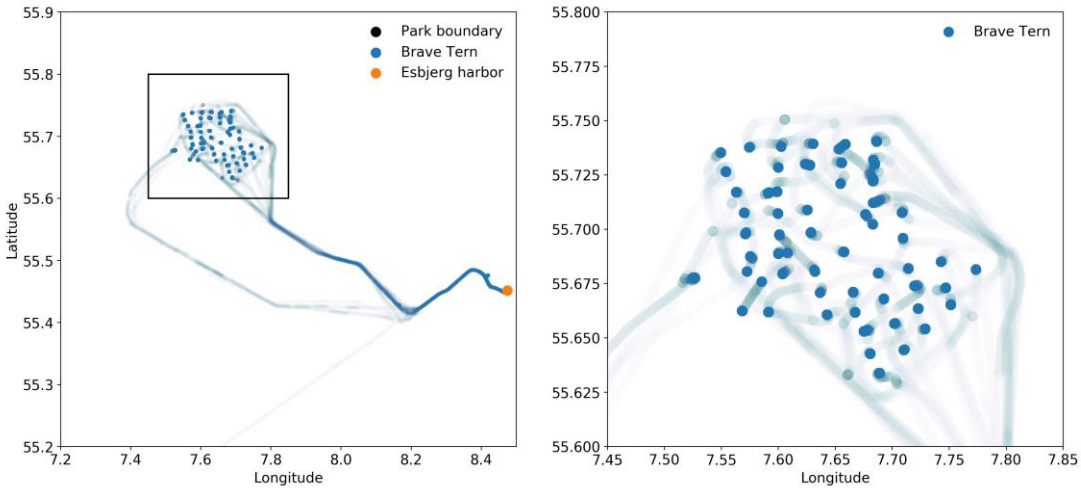
Analyzing and understanding AIS data has for some years been a part of a larger tracking project carried out internally in Siemens Gamesa. Until now the results generated from AIS data has relied on traditional scripting, which required fundamental knowledge of the individual offshore sites. All in all, the traditional scripting approach yields the same level of accuracy on results, but requires significantly more overhead in setting up and maintenance. The fact that the machine learning model is simpler to set up and maintain than traditional scripting was an eye opening experience contradicting the intuition of many project participants and therefore and experience worth sharing.

METHODS

2.1. DATA

We exclusively use AIS data, which reports unique identification, position, course and speed for marine vessels. This data can either be collected directly from vessel transponder broadcasts or obtained from aggregators such as maritime authorities or data brokers. For Danish waters, historical AIS data is currently made publicly available for free by the Danish Maritime Authority [8]. For wind farms outside Danish waters, we obtain AIS data from MarineTraffic [9]. In this study, we only consider GPS position data (latitude, longitude). As an example, the left part of Figure 1 shows latitude and longitude extracted from AIS data for the Brave Tern jackup vessel during installation of Horns Rev 3 from July 2018 to January 2019. The right part of the figure shows the same data when zoomed in on the farm. The sampling frequency of the AIS data, publicly available from [8], is approximately 0.1 Hz allowing for a very detailed tracking of the vessel.

Figure 1 Position data for the Brave Tern jackup vessel during installation of Horns Rev 3 from July 2018 to January 2019 (left). Zoomed in version corresponding to the black frame in the left part (right).



2.2. CLUSTERING

The current state-of-the-art method for determining offshore wind installation times entails dividing the time interval from start to finish of the entire farm by the number of turbines [12]. This method provides an average installation time, which includes the time spent in transit between the wind farm and harbor as well as the time spent in the harbor. The use of AIS data to determine installation times of offshore wind turbines was proposed in [12].

The new method presented here uses a machine learning method to cluster the GPS coordinates extracted from AIS data of jackup vessels. We are able to automatically identify installation times for individual turbines, which provides both an overall average, but also the distribution of installation times. In addition, we can identify the time spent in transit and the time spent in harbor, thus enabling a much more detailed description of the entire installation process.

We seek to determine installation times exclusively from AIS data since this is often the only data that is readily available to the public. Coordinates of individual turbines are generally not available. This can be remedied by applying a clustering algorithm to the GPS location data provided in the AIS broadcasts from every jackup vessel. Clustering of this data allows us to determine individual turbine coordinates and subsequently individual installation times.

Determining turbine locations is done using the K-means clustering algorithm as implemented in scikit-learn [13]. Briefly, it divides a set of observations into k clusters by minimizing

$$\min_{S} \sum_{i=1}^{k} \sum_{x \in S_i} \|\boldsymbol{x} - \mu_i\|^2, \tag{1}$$

where S_i is the subset of the data assigned to cluster i and μ_i the mean of this subset. Generally, the vector x can be n-dimensional. In this case it has just two dimensions: longitude and latitude. When applying the clustering algorithm to each of the wind farms in Table 1, the number of clusters k is set to the number of actual turbines within the farm plus a few extra to account for the paths to and from the farm. The purpose of the extra clusters is to capture unnecessary data points so they do not impact the desired clusters. The extra clusters have been tweaked manually for each farm based on visual inspection and are automatically discarded during the subsequent process of determining installation times for each turbine. For a detailed description of clustering methods and the K-means algorithm, see [14].

The AIS data includes a signal called Navigational Status. This signal reports whether the vessel is moving, anchored etc. This signal could potentially be used to determine the location of turbines. However, the crew manually reports this signal, and therefore it is prone to error.

2.3. IDENTIFYING INSTALLATION TIMES

Having identified turbine locations by clustering the AIS data we determine the installation time of each turbine based on the AIS data assigned to each cluster. We discard all positions that are further than 100 meters from the cluster center. The installation time is then determined as the time starting from the vessel entering this 100-meter radius of the turbine until it leaves. We observe a few cases of what appears to be more than one installation per turbine. These individual time segments are summed to one cumulative installation time per turbine location.

To account for low time resolution and missing data, we determine the uncertainty of the identified installation time by calculating the time interval from the first data point just before the vessel enters the 100-meter radius until the first data point just after the vessel has left the 100-meter radius. This 100-meter radius has been chosen with the criteria to be as small as possible while taking the typical size of a jackup vessel into account.

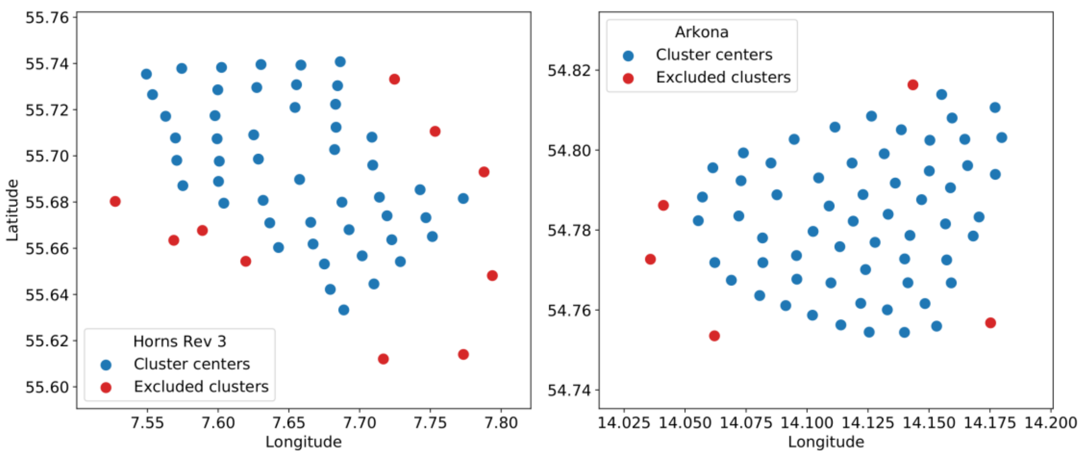
RESULTS

We apply the new method based on machine learning to 13 offshore wind farms in Danish, German and British waters as listed in Table 1. In the following subsections we first identify individual turbine locations. From these we determine individual installation times and compare these between the wind farms considered.

3.1. CLUSTERING

The results of applying the K-means clustering algorithm defined in Equation 1 to two wind farm installations in Danish waters are shown in Figure 2. The results for Brave Tern installing Horns Rev 3 and Sea Challenger installing Arkona are shown in the left and right panel, respectively. The figure shows the identified turbine locations from clustering AIS data in blue and additional clusters capturing the vessel's path to and from the wind farm in orange, which the algorithm has automatically marked for exclusion. The exclusion is based on the amount of data points within a cluster. The extra clusters contain much fewer data points for when the vessel is moving to and from the farm compared to being stationary during an installation.

Figure 2 Clustering of AIS data for Brave Tern installing Horns Rev 3 (left) and Sea Challenger installing Arkona (right).



3.2. INSTALLATION SEGMENTS

The installation times resulting from the clusters shown in Figure 2 are shown in Figure 3. The left panel represents Horns Rev 3 and the right panel Arkona, where the identified installations are sorted by duration.

The errorbars indicate the uncertainty in identifying the duration of each installation. This uncertainty depends on the temporal resolution and completeness of available AIS data. The two installations with a high uncertainty in Horns Rev 3 are caused by gaps in the AIS time series. For the remaining examples shown here the uncertainties are almost non-existent. This is due to the fact that the AIS data collected from [8] generally has a high sampling frequency.

Table 1 shows statistics on the identified installation times for each farm. We report the average, standard deviation, minimum, median and maximum times in hours. The coverage percentage is calculated as the number of identified turbine installations as a fraction of the actual number of turbines. These results are much more detailed than the current state-of-the-art of only reporting averages [12]. For all farms the median installation time is lower than the average, which is caused by a few outliers with a very long installation time. For most farms we are able to identify all turbines. The cases of missing turbines are due to missing data. The very high maximum installation time of 588 hours for Brave Tern at Hohe See is caused by 3 segments at the same location. They are each 295, 199 and 94 hours.

Figure 3 Installation times sorted by duration for Horns Rev 3 (left) and Arkona (right).

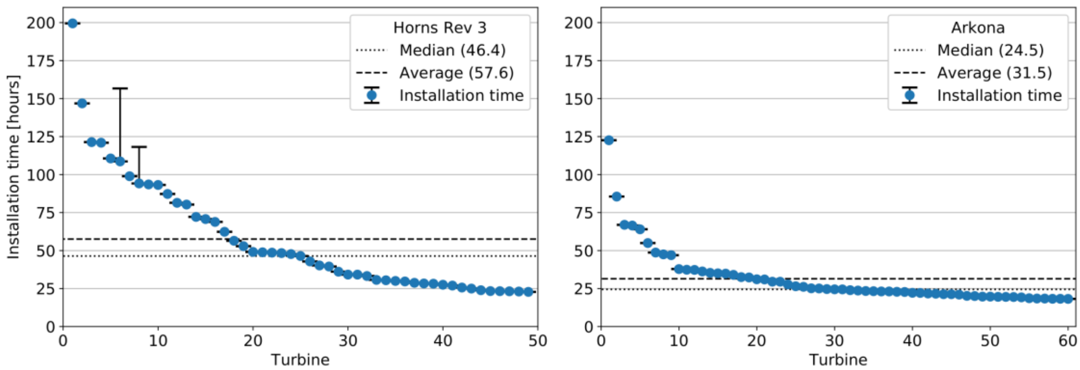


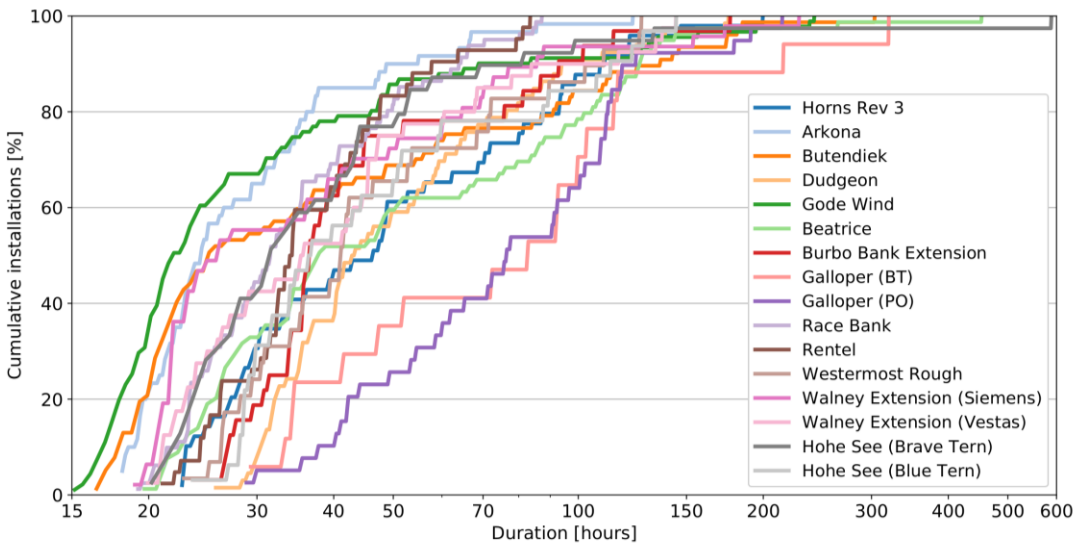
Table 1 Statistics on the identified installation segments for each farm. We report the average, standard deviation, minimum, median and maximum times in hours. The coverage percentage is calculated as the number of identified turbine locations as a fraction of the actual number of turbines.

Project	Avg.	s.d.	min	median	max	turbines	Coverage %
Horns Rev 3	57.6	38.1	22.8	46.4	199.5	49	100
Arkona	31.5	18.4	18.2	24.5	122.6	60	100
Butendiek	53.7	53.8	16.7	25.3	303.4	80	96
Dudgeon	57	33.4	25.9	43.2	175.4	67	99
Gode Wind	39.5	44.4	15.4	22.2	242.0	97	94
Beatrice	66.1	62.7	20.1	38.3	452.9	84	94
Burbo Bank Extension	50.4	33.2	23.9	36.8	176.5	32	100
Galloper (BT)	93.2	74.6	29.6	83.4	319.9	17	100
Galloper (PO)	84.8	43.3	29.0	76.8	214.6	39	100
Race Bank	37.2	16.7	19.3	31.6	87.2	91	89
Rentel	39	15.5	21.1	34.2	83.5	42	100

Westermost Rough	52.4	30.7	22.9	41.1	126.6	35	83
Walney Extension (Siemens)	46	42.5	19.2	26.2	228.6	47	100
Walney Extension (Vestas)	47.2	33.3	20.0	35.7	144.1	40	100
Hohe See (Brave Tern)	54.3	90.7	20.8	32.7	588.1	39	100
Hohe See (Blue Tern)	53.5	34.4	23.7	36.7	144.2	32	100

Figure 4 shows a comparison of the distribution of installation times across all wind farms. We see that most installation times are well below 100 hours and even below 50 hours, while there is a very small number of extreme cases with installation times of several hundred hours as shown also in Table 1. The figure shows a cumulative histogram of turbine installations per wind farm. As an example, it shows that for Gode Wind about 40% of the installations each took less than 20 hours and about 80% of the installations each took less than 40 hours. The steeper the curve, the lower the variation in installation times. The two leftmost curves for Gode Wind and Arkona are good examples of short installation times. On the other hand, the two curves to the right for Bold Tern and Pacific Orca installing Galloper show a large variations in installation times. Note that the x-axis is logarithmic and that all installations have been identified automatically, so they have not been manually validated individually.

Figure 4 Cumulative histogram of individual installation times compared between selected wind farms.



Similar to Figure 4, it is possible to compare the distribution of installation times between jackup vessels. However, individual installation times will vary based on factors such as the size and weight of the installed components, weather conditions, seabed, and the fact that the different jackup vessels have different lifting capacities. Additionally, the total installation time of the farm depends on the number of turbines the jackup vessel can carry per trip. Due to these factors such benchmarking should be done with caution.

Following the approach in [12], the average installation time per turbine for Horns Rev 3 is calculated by dividing the total time of installation (July 1st 2018 to January 21st 2019) by the number of turbines, which results in 100.6 hours per turbine. This is an increase of 87.9% compared with the average time reported in Table 1, because the approach in [12] does not take into account the time spent in transit and harbor. However, it is important to estimate both how much time is spent installing turbines and how much time is spent docked. This is due to the possibility of the rate of a jackup vessel being variable depending on the amount of crew required, which is reduced when docked for longer periods. Distinguishing between these different classes of time segments enables detailed modeling of offshore wind installation costs [15].

CONCLUSION

Based on the identified time intervals for installation, we determined the performance of the installation process for each wind farm. These results allow planners of future wind farm projects to base their cost estimates of installation times on generalizations of the results presented here. Increasing accuracy of cost estimates leads to reduced financial risk and thereby lowering the overall project costs. This analysis also enables identifying particularly efficient installations times in order to learn from them. Additionally, these results allow us to compare installation times between projects and benchmark the performance of different jackup vessels. However, such comparisons should be done with caution since the different wind farms use turbines of varying sizes and weight, which influence the expected installation times. Further, the different jackup vessels have varying lifting capacities limiting the availability of vessels for turbines of increasing size. Bad weather conditions also have an effect: high wind speeds or wave heights might cause delays in jacking up and lifting. Additionally, the quality of the seabed, in combination with the weight of the turbine components, significantly impacts the jackup and jack-down times.

Due to the number of factors affecting installation times it might not be straightforward to generalize the results on installation times in this study to future wind farms. However, the method presented here allows turbine manufacturers to continuously monitor their installation processes. This enables a continuous feedback loop where previous estimates of installation times can be evaluated. Such comparisons can in turn be used to improve the estimates for future offshore wind projects in an iterative way. This will lead to higher accuracy in predictions and, thus, lower project costs due to increasingly reduced risk.

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